

EfficientNet Deep Learning Model for Satellite Image Classification Using the EuroSAT Dataset

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Abstract

This study investigates the use of EfficientNet-B0, a computationally efficient convolutional neural network architecture, for satellite image classification using the EuroSAT dataset. Evaluating the baseline EfficientNet-B0 model, we achieved 98.1% overall accuracy and a 0.98 macro-averaged F1 score on the test set. This performance is highly competitive with state-of-the-art results reported for the EuroSAT dataset, demonstrating that EfficientNet-B0 offers a strong balance between high accuracy and computational efficiency. These findings suggest that EfficientNet-B0 is a promising approach for tasks requiring efficient satellite image categorization, such as large-scale land use monitoring, urban planning, and environmental management analysis based on satellite imagery.

Keywords

Satellite Image Classification, EfficientNet, Deep Learning, EuroSAT, Remote Sensing

1. Introduction

The Earth is composed of only about 29% land-continents and islands, and the remaining 71% is covered by water-saltwater bodies like oceans and seas as well as freshwater sources such as rivers or lakes: with 2% being made up by frozen forms such as ice caps or glaciers. Among the different types of lands, habitable land is the only one where one can live and produce things from it for example agricultural land which occupies about 70% pastureland and 30% arable land. Pasture, grazing land, rangelands, and meadows are primarily used for livestock rearing, whereas cultivated, arable, and croplands are designated for crop production. Manual classification of these various areas requires more time through image interpretation techniques [1] because localization costs too much money since data analysts don't want to do much digging around, so automation becomes necessary. This therefore calls for an effective automatic satellite image classification technique that involves learning different vegetation types e.g., agriculture, forests, etc., and studying urban-residential as well as commercial to determine different land uses in an area [2][3].

The significance of image interpretation from satellites has multiplied in different areas such as planning urbanization, agriculture and environmental monitoring. The demand for efficient and accurate ways of classifying this type of information is increasing in the face of ballooning satellite data volumes and improved quality. In urban planning, classification of satellite images helps create maps that highlight city configurations, debt infrastructure progress, or reveal land use patterns. Such knowledge helps to make informed choices concerning the allocation of resources and development needs for urban expansion. In addition, the agricultural sector uses these images to determine crop types variation, monitor their health conditions, note land cover changes among others which are useful in precision farming and management of crops. Furthermore, deforestation; desertification; water bodies alterations detection and analyses can be done through environmental monitoring based on these classifications. With an advancement in satellite technology comes a deeper richer data requiring sophisticated algorithms as well as machine learning techniques in order to manage these great volumes of information obtained.

Satellite imagery is a global effort to map worldwide communities such as OpenStreetMap [4], Google Earth [5], and Earth Explorer [6] which are platforms where maps are digitized using high-

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resolution images. These digitized maps act as living documents, where new features are added remotely by mappers located miles away while satellite pictures remain accessible to scientists across continents. Researchers have worked with various satellite image classification datasets like Landsat [7], Sentinel-2 [8], In-orbit [9], and RSI-CB256 [10] among others. Satellite imagery has a wide range of applications namely cartography and navigation [11], disaster response [12], and ecological monitoring [13]. These purposes can be achieved through highly accurate model satellite images.

This study investigates the use of EfficientNet, a state-of-the-art convolutional neural network architecture for classifying satellite images. In 2019, Tan and Le [14] developed an extremely effective image classification method known as EfficientNet which has been applied in many other fields too because it achieves excellent results while keeping computations at minimal levels. It is possible to make networks deeper, wider, or higher resolution through their compound scaling techniques, thus increasing both accuracy and efficiency beyond what traditional CNNs offer.

For this study, we utilize the EuroSAT dataset [15], a valuable resource for satellite image classification tasks. Recognizing the increasing need for methods that balance accuracy with computational efficiency in large-scale remote sensing, this research specifically evaluates the performance of the baseline EfficientNet-B0 architecture. By leveraging the EuroSAT dataset, we aim to establish a robust performance benchmark for EfficientNet-B0, assessing its ability to accurately classify diverse land use and land cover categories while capitalizing on its inherent efficiency. This evaluation helps determine its suitability for practical applications like land use monitoring and management strategies where both accuracy and processing speed are important considerations.

2. Related Works

With advances in satellite imaging and machine learning, land use and land cover (LULC) classification has made significant progress. LULC data is crucial for various applications, including urban planning, agriculture, forestry, and disaster management. Traditionally, LULC classification has relied on manual or semi-automatic methods that are time-consuming and prone to errors [16]. The integration of deep learning methods has improved both the efficiency and accuracy of classification tasks, enabling the analysis of large datasets [17].

The development of benchmark datasets has played a key role in advancing machine learning and computer vision research in remote sensing. Notable datasets such as the UC Merced Land Use Dataset [18] and BigEarthNet [19] have provided standardized benchmarks for training and evaluating models. These datasets have facilitated the comparison of algorithms, fostering innovation and progress in the field.

The EuroSAT dataset [15], is a benchmark dataset specifically designed for LULC classification tasks. EuroSAT has been widely used in various research contexts. Several papers have investigated alternative deep learning approaches. Yassine et al. [20] improved LULC classification from satellite imagery using deep learning techniques on the EuroSAT dataset, although they did not specify the architecture used. Similarly, Gunen [21] compared deep learning and machine learning methods for wetland water area determination using EuroSAT, highlighting the potential of deep learning but not focusing on a particular efficient architecture.

Kumari and Minz [22] explored the use of convolutional networks with focal loss optimization for LULC scene classification, also using the EuroSAT and Sentinel-2 datasets. Their work, however, differs from ours in its focus on loss function optimization rather than architectural efficiency.

Bhatt and Bhatt [23] proposed a novel methodology (DCRFF-LHRF) for efficient land cover classification on the EuroSAT dataset; however, their approach differs from ours in its methodological innovation rather than its specific choice of architecture.

Other research has focused on enhancing the EuroSAT dataset or exploring transfer learning techniques. Kunwar and Ferdush [24] investigated the application of transfer learning for LULC mapping using the EuroSAT dataset. Kurian et al. [25] similarly explored transfer learning approaches in remote sensing image classification, but without specific application to EuroSAT or a comparative study of various deep learning architectures. Gurav et al. [26] compared GAN-based methods for enhancing EuroSAT image classification, providing a complementary approach to improve classification accuracy.

The work by Honegger et al. [27] presented the EuroSAT Model Zoo, a valuable benchmark, but did not directly compare the performance of EfficientNet. Finally, while Ghoslatlou et al. [28] explored

active learning for Earth observation satellite image classification, their focus on active learning strategies contrasts with the focus of this study on the efficient architecture of EfficientNet.

This study distinguishes itself by providing a focused evaluation of the baseline EfficientNet-B0 variant's performance specifically on the EuroSAT dataset, analyzing its effectiveness in terms of both classification accuracy and its inherent computational efficiency. While previous works have applied various deep learning models [20-23, 27, 28] or transfer learning approaches [24, 25] to EuroSAT, or explored different aspects like loss functions [22] or data enhancement [26], few have systematically benchmarked the trade-offs offered by the lightweight, entry-level EfficientNet-B0. By establishing this performance baseline, our work provides a valuable reference point for assessing the practical utility of efficient architectures and for comparison against future, potentially more complex models developed for EuroSAT-based land cover classification.

3. Proposed Methodology

3.1. Dataset

The dataset, that used in the study, includes various categories such as annual crop, forest, herbaceous vegetation, motorway, industrial, pasture, permanent crop, residential, river, sea, and lake. The EuroSAT dataset is particularly suitable for this study due to its comprehensive coverage of European land cover types and its multispectral nature. This allows to evaluate the performance of EfficientNet on a variety of satellite imagery that closely mimics real-world applications. Furthermore, the balanced class distribution of the dataset allows a fair assessment of the classification capabilities of the model across different land use categories. EuroSAT consists of 27,000 labeled Sentinel-2 satellite images covering 13 spectral bands and 10 land use and land cover classes. The images are 64x64 pixels in size. Each class contains 2,000 to 3,000 images. Figure 1 shows the distribution of images in the dataset by class. Figure 2 provides examples of the dataset.

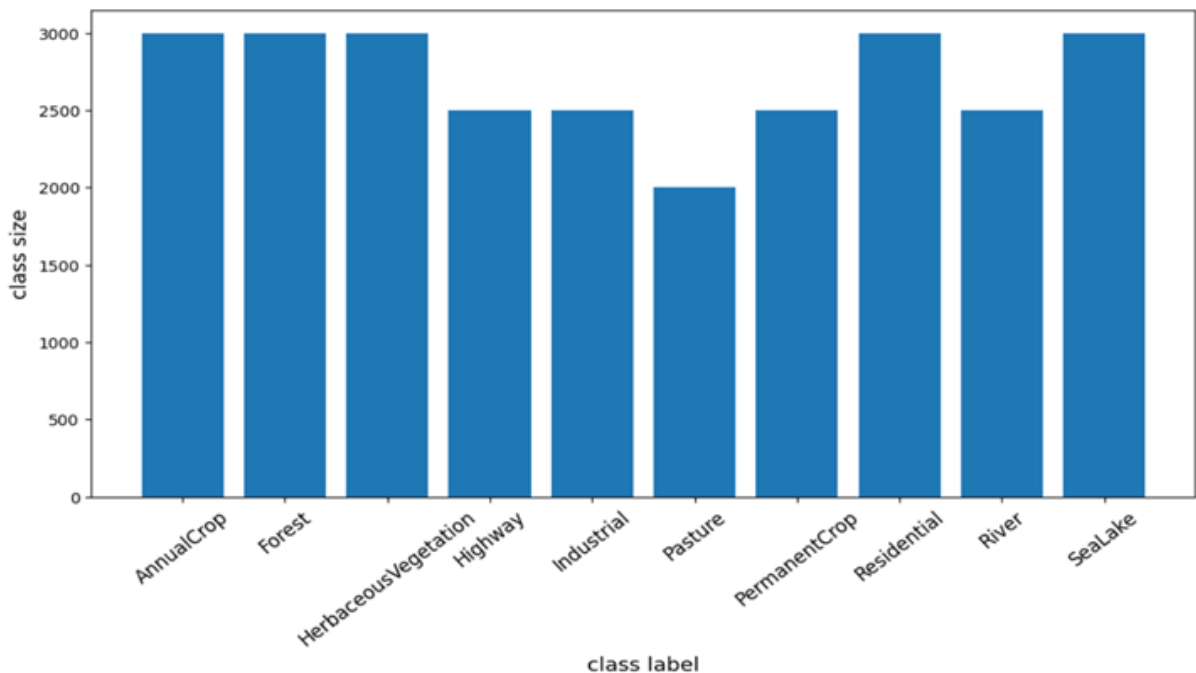


Figure 1: Distribution of images per class

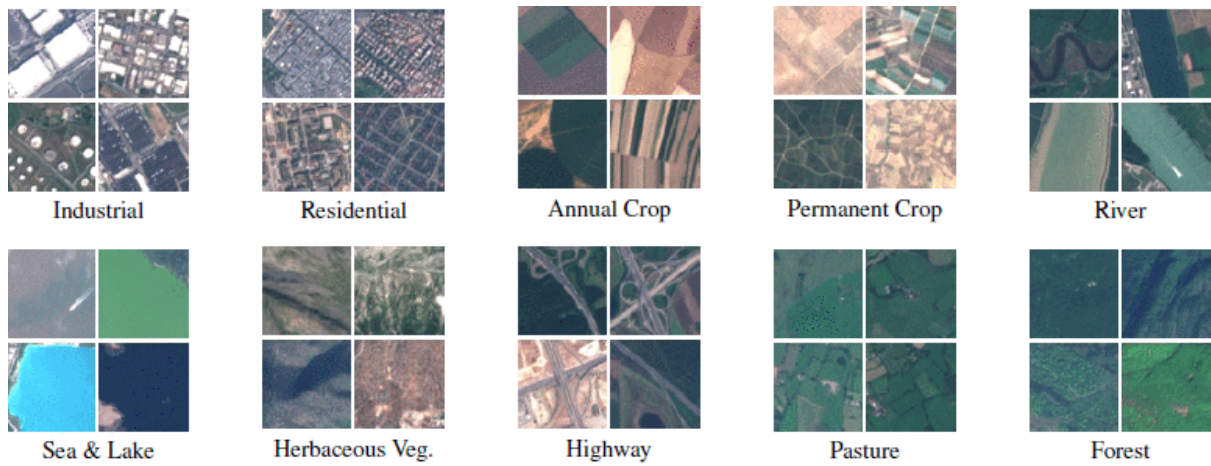


Figure 2: Samples of The EuroSAT Dataset [15]

The EuroSAT is a dataset of satellite imagery selected in relation to the cities covered in the European Urban Atlas. The cities covered are distributed over 34 European countries: Austria, Belarus, Belgium, Bulgaria, Cyprus, Czech Republic (Czechia), Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy/Holy See, Latvia, Lithuania, Luxembourg, Macedonia, Malta, Republic of Moldova, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, Ukraine and the United Kingdom. The distribution of the EuroSAT dataset is shown in Figure 3.

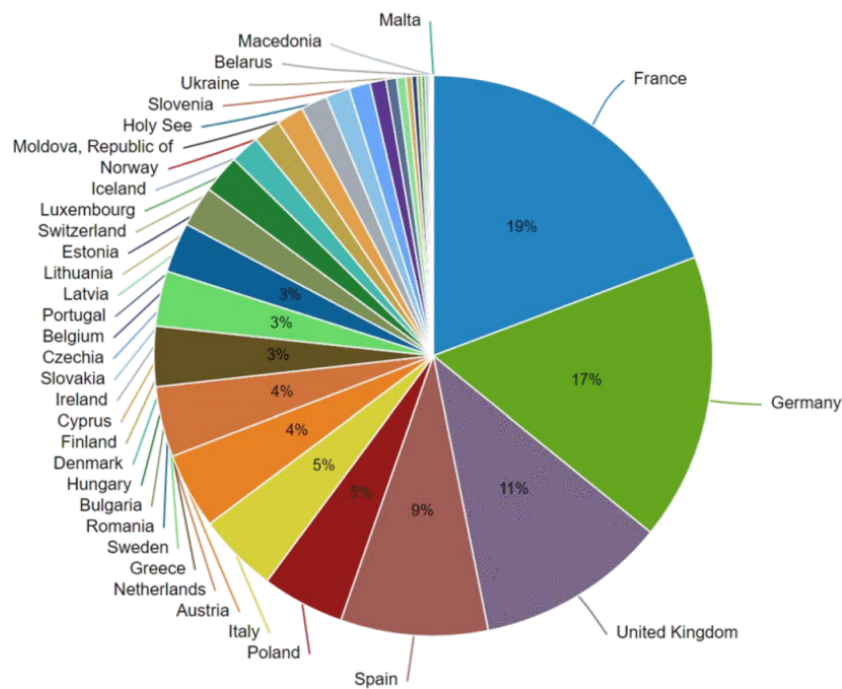


Figure 3: EuroSAT dataset distribution.[15]

The illustration in Figure 4 gives an overview of the process of patch-based land use and land cover classification using satellite imagery. A satellite scans the Earth's surface to collect images from the ground. From these images, small-sized image patches are used for the classification task. The aim is to automatically provide labels that identify the physical type of terrain or how the land is used. To do this, an image patch is fed into a classifier, in this case a neural network, and the classifier predicts the class shown on the image patch.

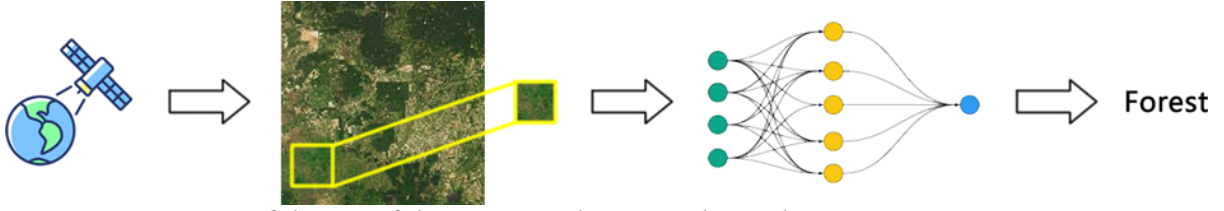


Figure 4: Overview of the use of the EuroSAT dataset in the study

3.2. EfficientNet

In this study, EfficientNet-B0 was selected as the primary model for classifying satellite images. As the baseline architecture within the EfficientNet series [14], it is specifically designed to optimize the balance between model complexity (depth, width, resolution) and performance effectively [29]. Our rationale for choosing B0 was to first establish a performance benchmark using the most computationally efficient member of this model family, providing insights into its suitability for resource-aware applications before potentially exploring larger, more computationally intensive variants. These networks rely on mobile inverted bottleneck convolution (MBConv) as their fundamental building blocks. MBConv incorporates a technique known as squeezing-and-excitation optimization. This method enhances the model's ability to recalibrate feature channels, thereby improving its overall performance in classification tasks.

EfficientNet-B0 uses activation functions that contribute to its efficiency. The model also includes depth-wise separable convolutions, allowing for reduced computational costs during training. This feature is particularly beneficial when handling large datasets, like satellite images. The model comprises seven distinct stages, each containing a varying number of layers, specifically between one and four layers, depending on the requirements of the stage.

The input layer of EfficientNet-B0 was adapted to suit the satellite image classification task effectively. This adaptation was necessary to accommodate the 13 spectral bands utilized in the EuroSAT dataset [30]. These bands represent different wavelengths of light, providing important information for land classification.

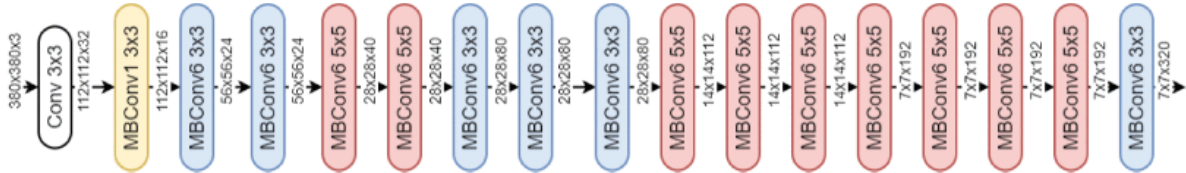


Figure 5: The architecture of EfficientNet b0[31]

At the end, the final classification layer is replaced by a new fully connected layer with ten output nodes corresponding to land use and land cover classes from the dataset. These nodes correspond to the specific land use and land cover classes defined in our dataset. This adjustment ensures that the model accurately reflects the categories to aim to classify. The initial weights of the model were set using pre-trained weights from ImageNet, a large and diverse image dataset. This process took advantage of transfer learning, allowing the model to adopt to the unique characteristics of the satellite images while retaining the knowledge gained from the ImageNet dataset. This strategic approach set the foundation for our satellite image classification efforts. Figure 5 provides an example structure of the model used in this study.

4. Experimental Results

The baseline model called EfficientNet-B0, achieved an overall accuracy of 98.1% on the EuroSAT test set. It demonstrates that EfficientNet is efficient for satellite image classification tasks, performing at a competitive level with state-of-the-art results on this dataset. At the end of training, loss, and accuracy graphs were obtained. These graphs are shown in Figure 6. The plot of loss reveals a significant drop-off of both train and validation losses across epochs as it gradually declines from initial high values. This trend shows good convergence, while the closeness between training and validation losses indicates that the model generalizes well without any symptoms of overfitting. The accuracy plot shows a clear upward trend with accuracy peaking above 90%. This means that as the model trains, its predictions

become more accurate over time. The steady improvement implies that further training could yield more benefits. Thus, these results prove that the model learns very well and generalizes effectively when applied to satellite image data.

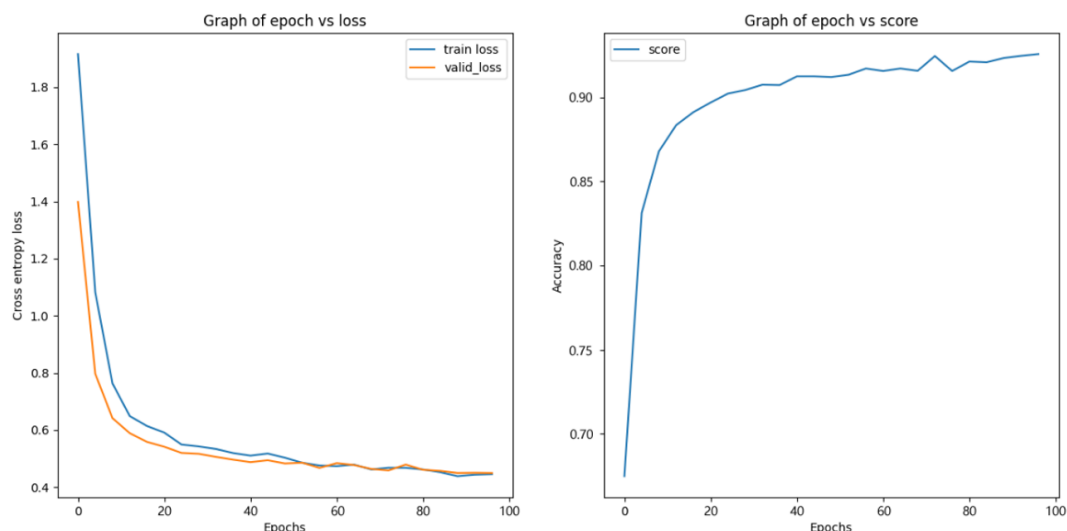


Figure 6: Loss and Accuracy graphs

The EfficientNet-B0 model showed strong performance on all 10-land use and land cover categories in the EuroSAT dataset, with F1-scores ranging from 0.96 to 1.00. The model excels in classifying different categories such as "PermanentCrop" and "River" due to their unique spectral signatures and homogeneous textures in satellite imagery. Classes such as "AnnualCrop", "Highway" and "SeaLake" also performed well with F1-scores of 0.99. The results for each class are shown in Table 1.

Table 1
Test Results

Class	Precision	Recall	F1 Score
AnnualCrop	0.99	0.99	0.99
Forest	0.96	0.98	0.97
HerbaceousVegetation	0.98	0.96	0.97
Highway	1.00	0.99	0.99
Industrial	0.97	0.96	0.96
Pasture	0.96	0.98	0.97
PermanentCrop	1.00	1.00	1.00
Residential	0.98	0.95	0.96
River	1.00	1.00	1.00
SeaLake	0.98	0.99	0.99

In Figure 7, the confusion matrix shows the classification performance of the EfficientNet B0 model on satellite images. The highest value along diagonal represents perfect accuracies with AnnualCrop, highway and permanent crops being particularly strong at; 0.99, 0.99 and 1.00 respectively. Thus, these values imply that a large number of these categories are correctly classified by this model with high precision. However, there is slight confusion, such as Forest being misclassified as Herbaceous Vegetation (1% of Forest samples) and Residential areas sometimes misclassified as SeaLake (3% of Residential samples). This suggests the model faces slight difficulties distinguishing between categories with potentially similar spectral characteristics (e.g., certain forest types vs. dense vegetation) or contextual elements (e.g., coastal residential zones, properties with large water features). Overall, the matrix demonstrates strong performance while highlighting specific areas where future work might yield improvements.

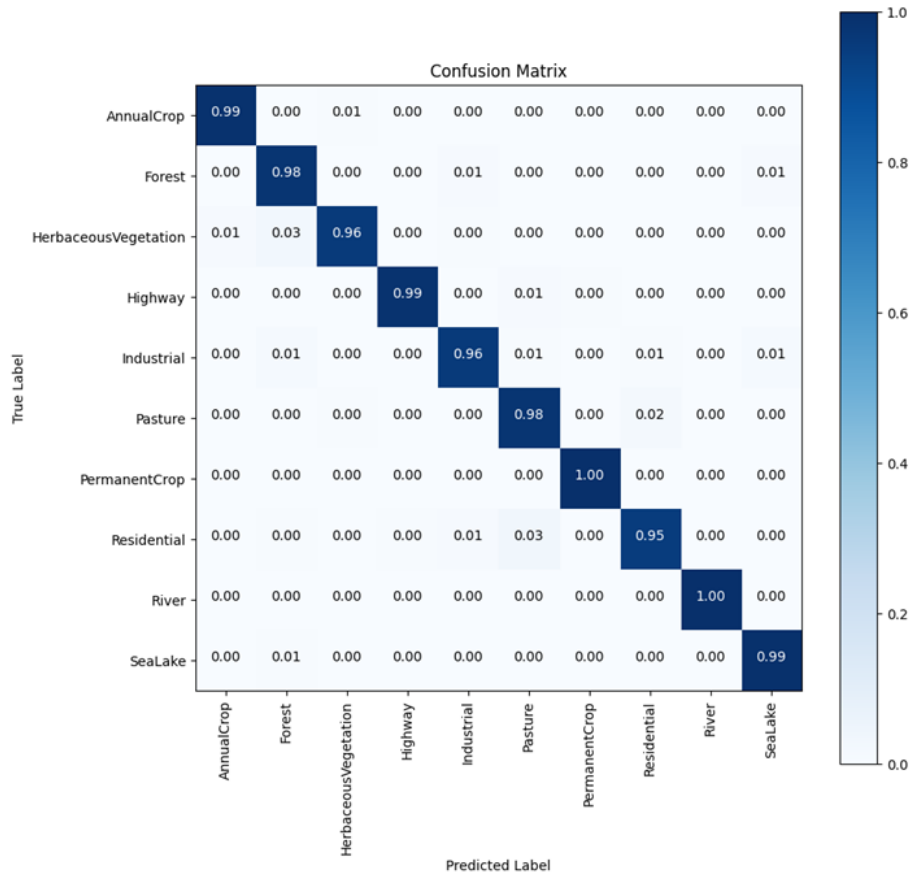


Figure 7: Confusion Matrix

5. Discussion

The experimental results clearly demonstrate that EfficientNet-B0 is a highly effective model for satellite image classification using the EuroSAT dataset. Achieving 98.1% overall accuracy and a 0.98 macro-averaged F1 score, its performance is competitive with, or exceeds, several reported state-of-the-art methods on EuroSAT, validating its capability. The performance across different classes was consistently high, with F1-scores ranging from 0.96 to 1.00, highlighting its robustness in distinguishing different landscape types.

One of the key advantages of EfficientNet-B0 is its computational efficiency, which is particularly relevant in remote sensing applications where handling large-scale satellite imagery is essential. The compound scaling approach of EfficientNet allows it to balance model depth, width, and resolution while maintaining strong performance. This efficiency, combined with the demonstrated high accuracy, makes it a compelling baseline, particularly for applications where computational resources may be constrained.

The confusion matrix analysis indicates that the model performs well across most categories, with particularly strong classification in classes such as PermanentCrop and River, likely due to their distinct spectral signatures. However, minor misclassifications were observed between Forest and Herbaceous Vegetation, as well as between Residential and SeaLake. These errors, potentially stemming from spectral similarities or contextual overlaps as noted in Section 4, and possibly influenced by the dataset's resolution, indicate areas for potential improvement. Future work could address these challenges by incorporating additional training data, fine-tuning hyperparameters, or leveraging ensemble learning techniques to further improve classification accuracy.

Additionally, while EfficientNet-B0 has proven to be a powerful and efficient baseline model, exploring other EfficientNet variants (such as B3 or B4) which trade some efficiency for potentially higher capacity [14], or applying advanced transfer learning techniques, could further enhance performance. Multi-spectral feature fusion, integrating different spectral bands from Sentinel-2, may also improve class separability, especially for challenging categories.

Overall, the findings suggest that EfficientNet is a promising architecture for satellite image classification, offering a balance between accuracy and computational efficiency. The results indicate their potential for large-scale automated remote sensing applications, paving the way for more efficient and accurate land cover monitoring in the future.

6. Limitations and Future Work

While this study demonstrates the effectiveness of EfficientNet-B0 for satellite image classification using the EuroSAT dataset, it is important to acknowledge certain limitations and potential avenues for future research. Understanding these limitations is crucial for interpreting the results within a broader context and guiding future efforts to improve the accuracy and applicability of satellite image classification techniques.

6.1. Dataset-Related Limitations

The EuroSAT dataset, while widely used and valuable, presents certain inherent limitations. The images are relatively low-resolution (64x64 pixels), which may limit the ability to distinguish fine-grained details and complex land cover patterns. This lower resolution may result in difficulties in classifying urban areas with dense buildings or agricultural areas with narrow fields, for example. Furthermore, EuroSAT represents a specific geographic region (Europe) and period. This may limit the generalizability of the trained model to other regions with different environmental conditions, agricultural practices, or land use patterns. The dataset's class balance, while generally good, may not perfectly reflect the real-world distribution of land cover types in all regions, potentially leading to biased performance in specific applications. Another aspect to consider is the reliance on Sentinel-2 imagery alone. Integrating other data sources, such as LiDAR data for elevation information or radar data for cloud penetration, could provide complementary information and improve classification accuracy, especially in cloud-prone regions.

6.2. Model-Related Limitations

EfficientNet-B0, while computationally efficient, is a relatively shallow model compared to some other deep learning architectures. More complex models, such as larger EfficientNet variants (B1-B7) or transformer-based models, may potentially achieve higher accuracy, especially on more challenging datasets or with higher-resolution imagery. However, increasing model complexity typically comes at the cost of increased computational requirements and a greater risk of overfitting, requiring careful regularization and validation strategies. The reliance on ImageNet pre-trained weights, while beneficial for transfer learning, may also introduce a bias towards features that are more common in natural images than in satellite imagery. Fine-tuning the model with a larger satellite-specific dataset or exploring alternative pre-training strategies could potentially mitigate this bias. Also, the current implementation does not explicitly address the spatial context of the images. Integrating spatial information, such as using contextual information from neighboring image patches, could improve classification accuracy, especially for land cover types that exhibit spatial dependencies (e.g., agricultural fields or urban areas).

6.3. Future Research Directions

Building upon the success of this study, several exciting avenues for future research emerge. A primary focus should be on expanding the datasets utilized in model training, incorporating larger, more diverse, and higher-resolution satellite imagery from various geographic regions. This could also involve leveraging multi-temporal data to capture seasonal variations and fusing data from multiple sensors like LiDAR and radar to enhance classification accuracy, particularly in cloud-prone areas. Moreover, exploring more advanced deep learning architectures, such as transformer-based models or hybrid CNN-transformer networks, holds the potential for improved performance by capturing long-range dependencies and contextual information more effectively. Developing domain-specific pre-training strategies tailored to satellite imagery characteristics, rather than relying solely on ImageNet pre-trained weights, could further enhance feature extraction. Addressing the challenges of uncertainty and explainability in model predictions is crucial, necessitating the

development of methods for quantifying and visualizing prediction uncertainties, as well as exploring explainable AI techniques to understand model decision-making processes. Furthermore, focusing on real-world applications and deployment in areas like land use monitoring and urban planning is essential, involving the creation of user-friendly tools and integration of models into existing workflows. Finally, exploring active learning strategies to reduce the need for vast labeled datasets and utilizing temporal analysis to detect land cover changes over time represents promising avenues for future investigation. By pursuing these directions, the field of satellite image classification can continue to advance, ultimately leading to more sustainable and effective management of our planet's resources.

7. Conclusion

EfficientNet-B0 has emerged as a highly compelling solution for satellite image classification when applied to the EuroSAT dataset. Achieving a robust overall accuracy of 98.1% and a macro-averaged F1 score of 0.98, the model demonstrates a strong capacity to effectively categorize ten distinct land use and land cover classes. This level of performance is comparable to state-of-the-art results reported in the literature for this dataset, establishing EfficientNet-B0 as a strong baseline contender. The consistently high F1-scores across the different classes, ranging from 0.96 to 1.00, further emphasize its reliability and potential for broad applicability in real-world scenarios where diverse landscapes are encountered. The observed reduction in training and validation losses throughout the training process reinforces the model's ability to generalize well and minimize misclassifications, indicating a robust learning process.

Beyond the accuracy metrics, the inherent computational efficiency of EfficientNet-B0 is a significant advantage. This efficiency allows for the processing of large-scale satellite imagery datasets without demanding excessive computational resources, a critical factor for practical deployment in operational settings. The model's ability to balance accuracy with computational cost makes it a valuable tool for applications where timely and cost-effective analysis is paramount.

The detailed confusion matrix analysis provides valuable insights into the model's performance, highlighting areas of strength and potential areas for refinement. While the model exhibits excellent performance, minor misclassifications between spectrally similar classes suggest areas for future refinement, potentially through strategies like incorporating additional data or multi-spectral fusion, as discussed. Exploring larger EfficientNet variants or more recent architectures may also yield improvements, likely with increased computational demands.

Looking forward, future research should focus on several key areas to further enhance the model's performance and broaden its applicability. First, addressing the observed misclassifications through strategies such as incorporating additional training data, especially for the less well-classified categories, could prove beneficial. Further optimization of the model's architecture, including fine-tuning hyperparameters specific to satellite imagery characteristics, may also yield improved results. Exploring alternative EfficientNet variants, such as B1, B3, or B4, or even experimenting with more recent architectures, could lead to increased accuracy, potentially at the expense of some computational efficiency. Furthermore, incorporating multi-spectral feature fusion techniques, leveraging the rich spectral information from the Sentinel-2 bands, could improve class separability and reduce ambiguity in classification, especially for the challenging land cover types. The use of data augmentation techniques could also be explored to improve model generalization and robustness.

In conclusion, this study validates EfficientNet-B0 as a powerful and efficient solution for satellite image classification on EuroSAT. The demonstrated performance, combined with identified avenues for future research, positions EfficientNet-based approaches as a promising pathway toward advanced and automated remote sensing capabilities, contributing valuable insights for the effective and sustainable management of our planet's resources.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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